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Componential Segmentation Based Conjoint Analysis: the Dummy-Coded Parametrization of the Model

Amedeo De Luca*

Università Cattolica del "Sacro Cuore", 20100 Milano, Italy

Abstract

In Componential Segmentation (CS) each component of each consumer profile, considered jointly with each component of the product profile, is supposed to contribute to the overall evaluation of the product. The CS focuses on the effect of interactions between the product profile **x** (a vector of dummy variables that describes the product) and the person profile **z** (a vector of dummy variables that describes the person in terms of a certain set of background characteristics) on preference for the product. A consumer's reaction to a product is broken into the sum of two components: 1) the average part-worth utilities due to the attribute levels of the product (pooled across all respondents in a market survey) and 2) the interactions between the consumer's background variables and the attribute levels.
In this paper we propose the dummy-coded parametrization of the model, easier to apply than other types of estimation suggested in the literature, and which provides two baselines (a new circumstance in the literature of the field): a first one related to the attributes of the product, a second one relating to the background characteristics. We provide an application of the model and an original interpretation of interaction effects.

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Keywords: Baselines; Componential Segmentation; Conjoint Analysis; Decompositive Model; Interaction effects; Dummy variables.

1. Introduction

In Componential Segmentation (CS) interest focuses on the interaction effect of person and product attribute levels to produce a response (*overall* evaluation) for various product descriptions, see Green (1977).

A person's reaction to a product is broken into the sum of two components: 1) the average part-worth utilities

* Corresponding author. Tel.: +0-039-02-72342952; fax: +0-039-7234-2671
E-mail address: amedeo.deluca@unicatt.it

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due to the attribute levels of the product, pooled across all respondents in a consumer research and 2) the interactions between the person's background variables and the attribute levels.

For the estimation of the part-worth utilities and interactions, Green and DeSarbo (1979) have proposed an approach so structured (Coseg-II model):

a) first, a pooled regression was run, with preference as the dependent variable and end effects coding of attributes as the independent variables, to estimate the aggregate part-worth utilities;

b) then a separate regression was run for each of the background variables, with the residuals from the pooled regression as the dependent variable and the interactions between the object profiles and the particular background variable - of time to time - as the independent variables (*stagewise regression*).

This approach involves burdensome iterations of calculation, as it does not estimate the interaction parameters simultaneously.

Later, Lauro et alii (2002) have proposed an approach to estimate the parameters which differs from the previous in the second step, since it estimates the interaction effects simultaneously and it uses - in order to identify the solution of the model - the Moore-Penrose generalized inverse for the experimental design of the attributes of the product ($\mathbf{G}_1^- = (\mathbf{X}'\mathbf{X})^-$) and for the background characteristics matrix of respondents ($\mathbf{G}_2^- = (\mathbf{Z}'\mathbf{Z})^-$), with heavy passages of matrix calculation (see Schott, 1997, p. 174).

In this paper, following the second approach, we propose the simple dummy variable coding of the product attributes and of the background characteristics, which allows an operational solution easier - in terms of matrix calculation - to estimate the parameters. In order to identify the solution of the model we drop, in the experimental design matrix ($\mathbf{X}$) and in the characteristics matrix of respondents ($\mathbf{Z}$), the first column of the dummy variables for each factor. Thus we come to two baselines joined (constant of the equation). This circumstance is new in the context of the identification of the solution of attitude models, which normally involve a single baseline; see, for example, De Luca et al. (2011). This parametrization of the model, by means of two baselines joint, requires an original interpretation of the interaction effects.

This paper also aims to provide a unified description of the CS methodology, by linking and integrating the two treatments (Green and DeSarbo (1979) and Lauro et alii (2002)), which - taken individually - are fragmented.

Paragraph 2 explains the methodology. Its application is illustrated in section 3, together with an interpretation of the model parameters, followed by the conclusions in section 4.

2. Methodology

Conjoint Analysis (COA) deals with preference data (ratings or ranks) expressed by persons or judges (consumers, potential buyers, etc.), in a consumer research, on a set of stimuli (products), described by attributes assuming different values (attribute-levels).

Aim of the COA is to evaluate the relative importance of attribute-levels by means of a decompositive model, where only the global preferences (*overall*) are known, see De Luca (2010). The estimation method attempt to find a set of part-worth utilities, that relate the attribute levels of an object to overall evaluation of the product.

Unlike the basic COA methodology, in CS, by Green (1977), each component of the product profile, considered jointly with each component of each consumer profile, is supposed to contribute to the overall evaluation of the product. The CS focuses on the effect of interactions between the product profile $\mathbf{x}$ (a vector of dummy variables that describes the object) and the person profile $\mathbf{z}$ (a vector of dummy variables that describes the person in terms of a certain set of background characteristics) on preference for the product.

Through this mechanism one is able to predict how a person with a certain set of background characteristics will react to a particular product.

Thus, a consumer's reaction to a product is broken into the sum of two components:

1) the average part-worth utilities due to the attribute levels of the product, pooled across all persons;

2) the interactions between the consumer's background variables and the attribute levels.

The part-worth utilities and interactions are estimated by the following equation, see Moore (1980):

$$\boldsymbol{Y_i} = \sum_{j=1}^{K} \hat{\boldsymbol{\beta}}_j \boldsymbol{x_{ij}} + \sum_{h=1}^{S} \sum_{j=1}^{K} \hat{\boldsymbol{\gamma}}_{jh} \boldsymbol{x_{ij} z_h} + \boldsymbol{e} \qquad (1)$$

were:

Y_i is the preference for the i-th object or product (i = 1, 2, …, Q). The objects are described in terms of K_j (j = 1, 2, …, J) levels of J attributes. The i-th object is represented by a vector of dummy variables $\mathbf{x}_i = (x_{i1}, x_{i2}, \dots, x_{iK})$, where $K = \sum_{j=1}^{J} K_j$;

β_j is the part-worth utility estimate of the jth attribute level;

x_{ij} is the dummy variable corresponding to the i-th product and to the level j-th of the generic attribute of the product ;

$\hat{\gamma}_{jh}$ is the interaction between the attribute level of the i-th product represented by x_{ij} and the background variable level represented by z_h. The person's background variables can be represented by a vector of dummy variables $\mathbf{z} = (z_1, z_2, \dots, z_S)$, were $S = \sum_{h=1}^{H} M_h$ (M_h is the number of levels of the external variable h-th; h = 1, 2, …, H);

e is the error term.

2.1. Dummy variables coding of the matrices of the model

The multivariate regression model corresponding to (1) is estimated by the metric approach in the following two steps:

1) modelization of the preference and estimation of part-worth;
2) explanation of the part-worth utilities estimated by background variables.

Due to the peculiar structure of the design matrix **X** (in which the objects are described in terms of K_j levels of J attributes, in dummy variables coding), it can be seen that it is rank deficient and consequently we cannot compute the inverse of the matrix **X'X**.

In order to identify the solution we propose the use of the inverse of $\tilde{\mathbf{X}}'\tilde{\mathbf{X}}$, where $\tilde{\mathbf{X}}$ is a full-rank matrix obtained by dropping one column - the first - for each factor (*reference category*); the columns dropped compose, together, the first *baseline* (constant term), see Suits (1959).

Similarly, from matrix **Z'** of socio-demographic characteristics in dummy variable coding, we pass to the matrix $\tilde{\mathbf{Z}}'$ (full-rank matrix), obtained by dropping one column (the first, *reference category*) for each background variables; the columns dropped compose, together, the second *baseline* (constant term).

2.2. Estimation model

Starting with the two-stage approach by Lauro et alii (2002), modified according to the coding with dummy variables - here proposed - for matrices **X** and **Z**, the part-worth utilities and interactions are estimated by the following model:

$$\begin{cases} \mathbf{Y}_{Q\times G} = \tilde{\mathbf{X}}_{Q\times K}\hat{\mathbf{B}}_{K\times G} + \mathbf{E}_{Q\times G} \\ \hat{\mathbf{B}}'_{G\times K} = \tilde{\mathbf{Z}}'_{G\times S}\hat{\mathbf{\Theta}}_{S\times K} + \mathbf{F}_{G\times K} \end{cases} \tag{2}$$

were:

$\mathbf{Y}_{Q\times G}$ = overall evaluation matrix;

$\tilde{\mathbf{X}}_{Q\times K}$ = full-rank design matrix in dummy variable coding, obtained by dropping one column (the first) for each factor;

$\hat{\mathbf{B}}_{K\times G}$ = matrix of part-worth utilities for each level of each attribute for each judge;

$\tilde{\mathbf{Z}}'_{G\times S}$ = full-rank matrix of socio-demographic characteristics in dummy variable coding, obtained by dropping one column (the first) for each background variables;

Q = number stimuli;

K = number attribute levels of the product;

G = number judges;

$\hat{\mathbf{\Theta}}_{S\times K}$ = matrix of the interaction effects between the attribute levels of the product and the background variable levels;

S = number socio-demographic groups, after the suppression of the first column for each attribute/variable;

$\mathbf{E}_{Q\times G}$ and $\mathbf{F}_{G\times K}$ are the error matrix.

The solution of the system (2) is described below.

First, a pooled regression is run, with overall evaluation as the dependent variable and disjunctive binary coding of attributes as the independent variables, to estimate the aggregate part-worth utilities.

After, a multivariate regression is run, with the estimated part-worth utilities as the dependent variable, and binary coding of socio-demographic characteristics as the independent variables, to estimate the socio-demographic group part-worth utilities.

Each value $\hat{\boldsymbol{\theta}}_{\boldsymbol{h}\times\boldsymbol{k}}$, generic term of $\hat{\boldsymbol{\Theta}}_{S\times K}$ in the (2), can be interpreted as a measure of the preference of the *s-th* socio-demographic group (market segment) for the *k-th* attribute level of the product.

3. Application of the model: data and results

We now consider an illustrative application of the dummy-coded parametrization of the CS model proposed here. In this study we are interested in how subjects evaluate various kinds of coffeepot.

The respondents background variables and the attributes used to describe the coffeepot are given in Figure 1.

The full factorial design of product profiles (Addelman, 1962) is composed of 48 stimuli (ie: 2×2×2×2×3), utilizing the five attributes shown in Figure 1.

From this factorial plan was extracted a set of 12 stimulus card descriptions (¼ fractional full factorial design), with statistical randomness (see De Luca, 2004), shown in Table 1.

Hundred forty-four persons took part in the CS study. They were asked to rate their preferences on a 1 to 7 equal interval scale for each of 12 hypothetical coffee pots.

The sample design is the *quota sampling* (with *combined* shares), relating to 24 (corresponding to the cartesian product 2×2×2×3) of sample cells (arising from the combination of the levels of the four background variables observed on respondents and shown in Figure 1), with six replications of each of the 24 sample cells (see Fig. 3).

Therefore, the basic data are presented in a matrix 144×9.

Background variables and levels

Sex	Employment status	Number of family members	Age
1. *Male*	1. *Employed*	1. *1-2*	1. *30-35 years old*
2. *Female*	2. *Unemployed*	2. *> 2*	2. *36-60 years old*
			3. *over 60 years old*

Product attributes and levels

Lid coffeepot	External finishing	Handle antiscorch	Number cups
1. *Aluminum*	1. *Alluminum*	1. *Yes*	1. *Two*
2. *Transparent*	2. *Anthracite color*	2. *No*	2. *Four*

Price
1. *€ 14,90*
2. *€ 19,90*
3. *€ 24,90*

Fig. 1. Background variables and levels, product attributes and levels

The Figure 2 shows the design matrix $\mathbf{X}$ of the ¼ fractional randomized factorial design in binary coding.

Figure 3 shows an excerpt of the matrix socio-demographic characteristics ($\mathbf{Z}'$) in binary coding, utilizing the four attributes shown in Fig. 1.

Table 1. Fractional randomized factorial design of a coffeepot

Products	Lid coffeepot	External finishing	Handle antiscorch	Number cups	Price
1	*Aluminum*	*Anthracite*	*No*	*Four*	*€ 14,90*
2	*Aluminum*	*Alluminum*	*No*	*Four*	*€ 19,90*
3	*Aluminum*	*Alluminum*	*Sì*	*Four*	*€ 19,90*
4	*Transparent*	*Anthracite*	*No*	*Two*	*€ 14,90*
5	*Aluminum*	*Anthracite*	*Sì*	*Four*	*€ 24,90*
6	*Transparent*	*Alluminum*	*Sì*	*Two*	*€ 19,90*
7	*Transparent*	*Anthracite*	*Sì*	*Two*	*€ 24,90*
8	*Aluminum*	*Anthracite*	*Sì*	*Two*	*€ 19,90*
9	*Transparent*	*Anthracite*	*No*	*Four*	*€ 19,90*
10	*Transparent*	*Alluminum*	*No*	*Two*	*€ 19,90*
11	*Transparent*	*Alluminum*	*Sì*	*Four*	*€ 24,90*
12	*Aluminum*	*Alluminum*	*No*	*Two*	*€ 14,90*

$\mathbf{X}_{12,11} =$

Card n.	Lid coffeepot		External finishing		Handle antiscorch		Number cups		Price		
	Aluminum	*Transparent*	*Aluminum*	*Anthracite color*	*Yes*	*No*	*Two*	*Four*	*€14,90*	*€19,90*	*€24,90*
1	1	0	0	1	0	1	0	1	1	0	0
2	1	0	1	0	0	1	0	1	0	1	0
3	1	0	1	0	1	0	0	1	0	1	0
4	0	1	0	1	0	1	1	0	1	0	0
5	1	0	0	1	1	0	0	1	0	0	1
6	0	1	1	0	1	0	1	0	0	1	0
7	0	1	0	1	1	0	1	0	0	0	1
8	1	0	0	1	1	0	1	0	0	1	0
9	0	1	0	1	0	1	0	1	0	1	0
10	0	1	1	0	0	1	1	0	0	1	0
11	0	1	1	0	1	0	0	1	0	0	1
12	1	0	1	0	0	1	1	0	1	0	0

Fig. 2. Matrix of the fractional randomized factorial design of product profiles in binary coding

$\mathbf{Z}'_{144,9} =$

Judge n.	Sex		Employment status		Number of family members		Age		
	Male	*Female*	*Employed*	*Unemployed*	*1-2*	*> 2*	*30-35 years old*	*36-60 years old*	*over 60 years old*
1	1	0	0	1	1	0	0	0	1
2	1	0	0	1	1	0	0	0	1
3	1	0	0	1	1	0	0	0	1
4	1	0	0	1	1	0	0	0	1
5	1	0	0	1	1	0	0	0	1
6	1	0	0	1	1	0	0	0	1
7	0	1	1	0	0	1	1	0	0
8	0	1	1	0	0	1	1	0	0
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
138	1	0	0	1	1	1	0	0	0
139	0	1	1	0	0	1	0	0	1
140	0	1	1	0	0	1	0	0	1
141	0	1	1	0	0	1	0	0	1
142	0	1	1	0	0	1	1	0	0
143	0	1	1	0	0	1	1	0	0
144	0	1	1	0	0	1	1	0	0

Fig. 3. Matrix of the socio-demographic characteristics in binary coding

Figure 4 shows an excerpt of the matrix that reports the overall evaluation judgment y_g (g = 1, 2, …, 144) expressed by each respondent on the 12 product profiles.

$$\mathbf{Y}_{12,144} = \begin{array}{c|cccc|} \text{Judge n. / Card n.} & y_1 & y_2 & \dots & y_{144} \\ \hline 1 & 6 & 5 & \dots & 7 \\ 2 & 4 & 3 & \cdots & 4 \\ 3 & 5 & 4 & \cdots & 4 \\ \vdots & \vdots & \vdots & \cdots & \\ 12 & 5 & 4 & \dots & 4 \end{array}$$

Fig. 4. Overall evaluations matrix

As already noted in paragraph 2.1, in order to identify the solution of the model, we pass from the matrices $\mathbf{X}_{12,11}$ and $\boldsymbol{Z}'_{144,9}$ to full rank matrices $\widetilde{\mathbf{X}}$ and $\widetilde{\mathbf{Z}}'$, respectively, and we apply the two-step approach (2), as described below, in environment Microsoft Excel 2010 Programming Language.

In the first step of the (2) the subjects'overall evaluative responses $\mathbf{Y}_{12\times144}$ (assumed to be interval-scaled) are first regressed - on all respondents - on the dummy variable predictors representing the product attributes ($\widetilde{\mathbf{X}}_{12\times7}$).

The average part-worth utilities $\left(\widehat{\mathbf{B}}_{7\times144}\right)$ due to the attribute levels of the product are obtained by applying the classical principle of ordinary least squares (OLS), that is, using the following formula:

$$\widehat{\mathbf{B}}_{7\times144} = (\widetilde{\mathbf{X}}'_{7\times12} \cdot \widetilde{\mathbf{X}}_{12\times7})^{-1} \cdot \widetilde{\mathbf{X}}'_{7\times12} \cdot \mathbf{Y}_{12\times144}$$

In the second step of the (2) a multivariate regression is run, with the estimated part-worth utilities - in the first step - as the dependent variable $\left(\widehat{\mathbf{B}}'_{144\times7}\right)$, and dummy variable of socio-demographic characteristics $\left(\widetilde{\mathbf{Z}}'_{144\times6}\right)$, as the independent variables, to estimate the socio-demographic group part-worth utilities ($\widehat{\mathbf{\Theta}}_{6\times7)}$); these ones are obtained by applying again the OLS principle, that is, using the following formula:

$$\widehat{\mathbf{\Theta}}_{6\times7} = (\widetilde{\mathbf{Z}}_{6\times144} \cdot \widetilde{\mathbf{Z}}'_{144\times6})^{-1} \cdot \widetilde{\mathbf{Z}}_{6\times144} \cdot \widehat{\mathbf{B}}'_{144\times7}$$

Then we get, finally, the parameter estimates (interaction effect coefficients) shown in Table 2.

Each value $\widehat{\boldsymbol{\Theta}}_{\boldsymbol{h}\times\boldsymbol{k}}$, generic term of $\widehat{\mathbf{\Theta}}_{\mathbf{6}\times\mathbf{7}}$ in the (2) is interpreted as a measure of the preference of the *h-th* (h = 2, 3, …, 6) socio-demographic group (market segment) for the *k-th* (k = 2, 3, …, 7) attribute level of the product; in correspondence to h =1 and k = 1 we have the two baselines.

The results model, that is the interaction effects (with respect to the *baselines*) between the product attributes and person background, are given in Table 2.

In the reading and interpretation of the meaning of the coefficients in Table 2 must be taken in mind the two baselines, made up - respectively - by suppressed levels (first columns of each factor) in the matrix $\mathbf{X}$ of the product profiles in binary coding (*Baseline 1*), see Figure 2, and by suppressed levels (first columns of each variable) in the matrix $\mathbf{Z}'$ of the socio-demographic characteristics (*Baseline 2*), see Figure 3.

Such two baselines are formed:

- for the product factors (*Baseline 1*) by the following levels suppressed: *Aluminum* of factor Lid coffeepot, *Aluminum* of External finishing; *yes* of Handle antiscorch; *two* of Number cups; *€ 14,*90 of Price;
- for the socio-demographic variables (*Baseline 2*) by the following levels suppressed: *Male* of variable Sex, *Employed* of Employment status; *1-2* for Number of family members); *30-35 years old* of Age.

These baselines make up the constant term of the regression equations (4,769), see Table 2. This constant term in Table 2 appears at the intersection of the first row and first column of numeric values (row and column marked with darker color in the table).

Then, in Table 2, in the first line we read the relative effects (values of deviations from the constant equal to 4,769), with respect to constant term, of the attribute levels of the product shown.

Therefore, for example: the effect coefficient associated with the level *Transparent* of factor Lid coffeepot, equal to 0,288, indicates the value (relative effect) to add to the constant (4,769) to achieve the absolute effect size (equal to 4,769 + 0,288 = 5,057), of this level, on the overall evaluation of the product profile.

Table 2. Estimation results for componential segmentation model in relation to various profiles of coffeepot and socio-demographic characteristics of the evaluators

Product attributes → / Background variables ↓		*Baseline 1°*	Lid coffeepot *Transparent*	External finishing *Anthracite*	Handle anti-scorch *No*	Number cups *Four*	Price *€ 19,90*	Price *€ 24,90*
	*Baseline 2**	4,769	0,288	0,292	-1,203	0,375	-0,309	-1,056
Sex	*Female*	0,154	0,087	-0,064	0,154	0,035	-0,127	0,063
Employment status	*Unemployed*	0,038	-0,010	-0,030	-0,304	-0,188	0,380	0,618
Number of family members	*> 2*	-0,024	0,045	0,162	-0,024	-0,056	-0,026	-0,007
Age	*36-60 years*	0,370	0,010	-0,878	-0,221	0,193	-0,263	0,010
	over 60 years	0,696	-0,115	-1,117	-0,480	0,432	-0,451	-0,656

Baseline 1°: *Alluminium* for Lid coffeepot, *Alluminium* for External finishing, *Yes* for Handle antiscorch, *Two* for N. cups, *€ 14,90* for Price.
*Baseline 2**: *Male* for Sex, *Employed* for Employment status, *1-2* for Number of family members, *30-35 years old* for Age.

In the first row of numeric values in Table 2 also we observe that the presence of the category *Anthracit*e has a positive relative effect (0,292) on the overall evaluation; as are the category *Four* of factor Number cup (0,375).

Conversely, the category *No* for Handle anti-scorch has a negative effect (-1,203) on the overall evaluation, as well as the level € 19,90 (-0,309) of Price and even more the level € 24,90 (-1,056).

Likewise, in the first column of numeric values of Table 2 we read the relative effects with respect to constant term (values of deviations from 4,769) of the categories of the socio-demographic variables.

Therefore, for example: the effect coefficient associated with the level *Female* of the factor Sex, equal to 0,154, indicates the value (relative effect) to add to the constant (4,769) to achieve the effect in absolute effect size (equal to 4,769 + 0,154 = 4,923) of this level, on the overall evaluation of the product profile.

In the first column of numeric values in Table 2 also we observe that the presence of the category *Unemployed,* of Employment status, has a positive relative effect (0,038) on the overall evaluation; as are the category *36-60 years old* (0,370) and *over 60 years old* (0,696) of Age. Conversely, the category '*> 2*' of Number of family members has a negative effect (-0,024).

Also all other values that appear in Table 2 indicate the interaction effects (deviations from the constant term of the model); they correspond to the various combinations of the levels of the product attributes with the levels of the background variables.

From the Table 2 it is observed that the interactions between background variables and product attributes indicate that people with different background variables have different utilities for levels of the product attributes.

In conclusion, from the values of the interaction coefficients of the table we detect what is described below.

The women prefer the *Transparent* Lid coffeepot (relative effect of interaction equal to 0,087) more than men (relative effect of interaction for men is equal 0: reference category). The women prefer the category *No* (0,154) of Handle anti-scorch, category *Four* (0,035) of Number cups and level *€ 24,90* (0,063) of Price, more than men.

Conversely, the women prefer less than men (relative effect of interaction for men is equal 0: reference category) the category *Anthracite* (-0,064) of External finishing and level *€19,90* (-0,127) of Price.

The *Unemployed* prefer less of employed (reference category) the levels: *Transparent* (-0,010) of Lid coffeepot, *Anthracite* (-0,030) of External finishing, *No* of Handle anti-scorch (-0,304), *Four* (-0,188) of Number cups. On the contrary, the *Unemployed* prefer the higher price levels (interaction coefficient equal to 0,380 for level *€ 19,90* and equal to 0,618 for level *€ 24,90*).

The families with number of components greater than *two* prefer the category *Transparent* (0,045) of Lid coffeepot and *Anthracite* (0,162) of External finishing.

The judges of *36-60 years old* prefer more than respondents of *30-35 years old* (reference category) the levels: *Transparent* (0,010) of Lid coffeepot*, Four* (0,193) of Number cups and *€ 24,90* (0,010) of Price; while the judges of *over 60 years old* prefer most than respondents of *30-35 years old* (reference category) the levels: *Four* (0,432).

4. Conclusions

Within of the CS methodology (that analyzes the interaction of product and person attributes) based on the COA, in the study we propose the dummy-coded parametrization of the model, easier to apply than other types of estimation suggested in the literature, and which provides two baselines joint. The parametrization of the model requires an original interpretation of the interaction effects. An illustrative application that assesses the interaction effects between the product profiles (e.g., price) and the people profiles (e.g., sex), with reference to a consumer product, is provided. These interaction effects indicate that the people with different background variables have different utilities for levels of an attribute**.** In this way one is able to predict how a person with a certain set of background characteristics will react to a particular product. The increase in explanatory power achieved through the addition of the interaction variables gives some very useful indications about the segmentability of the market.

The study open up the possibility for extensions of the model: if consumers can be selected according to various kinds of fractional factorials (e.g., orthogonal main effects design), efficient designs can be constructed for both products and respondents.

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